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Enhancing the Precision of Daily Precipitation Data Using an ANN Downscaling Model: Case Study in Japan

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Synopsis

This study presents an artificial neural network (ANN)-based downscaling model aimed at enhancing the precision of daily precipitation data. The study employed 112 years of observed daily data, downscaling from a pseudo-coarse spatial resolution of 20 km to a finer spatial resolution of 5 km. The area covered was a square grid of 3x3 at 20 km resolution and the target of downscaling was the center grid of this square. The ANN model was trained using 85 years of data, tested over 12 years, and validated over 15 years in five regions across four seasons in Japan. The results of the study demonstrated a high level of agreement between the downscaled and original daily data over all regions and seasons, with the highest and lowest root mean square error (RMSE) being 3.4 mm/day and 0.12 mm/day, respectively. In addition, the ANN model successfully preserved the statistical properties of the original daily data, maintaining a mean and standard deviation bias within ±8%.

Keywords: Artificial Neural Networks; statistical downscaling; precipitation; spatial correlation

1. Introduction

The impact of climate change should be considered for better management of energy and water resources. The foremost hydro-climatological factors, temperature and precipitation, play a crucial role in hydrological research and the design of hydraulic infrastructures. Predicting potential shifts in these parameters, particularly for the future, is crucial for mitigating the dangers posed by droughts and floods (Nourani et al., 2019). General circulation models (GCMs) were used to obtain such data. However, the outputs of the GCMs are at coarse resolution and their direct use for regional/local studies is difficult (Vu et al., 2016). Accordingly, the GCMs outputs were downscaled to a finer resolution to fill this gap.

As for Japan, Meteorological Agency (JMA) and the Meteorological Research Institute (MRI) have developed Atmospheric General Circulation Models (AGCMs) with different spatial resolutions: globally 60 km, locally 20 km, and ongoing 5 km for Japan area. The river basins in Japan span over several hundred square kilometers in area. Accordingly, getting precipitation data at 5km resolution proves to be effective and useful. However, the limited diversity of ensemble outputs from 5 km compared to 20 km impedes its applicability in impact assessment research.

Basically, there are two main methods for downscaling of precipitation: dynamical and statistical (Wilby et al., 1998). The former is physically-based and it is computationally expensive. Consequently, statistical downscaling is widely used. Many studies have discussed the hypothesis of statistical downscaling and its type, advantages, and limitations (Wilby et al., 1997; 1998; 2004; Storch et al., 2013; Trzaska and Schnarr, 2014).

Among the many statistical downscaling methods currently used, the artificial neural network (ANN) is one of the most popular tools because of its efficiency and prompt operation. Vu et al. (2016) employed an ANN to downscale the monthly precipitation from four GCMs over Bangkok during the rainy season. The ANN model was trained using the selected predictors from the European re-analysis interim dataset (ERAI), and the trained ANN was applied to the dominant predictors from selected GCMs to downscale the precipitation for current and future predictions. This study demonstrates the applicability of ANN for precipitation downscaling, as a good agreement was found between downscaled and station observed data for the present time, with a correlation coefficient of 0.8. Sachindra et al. (2018) used four machine learning techniques to downscale monthly precipitation over 48 stations in Australia: genetic programming (GP), support vector machine (SVM), relevance vector machine (RVM), and ANN. The study suggests that RVM and ANN are suitable for floods, whereas RVM can be recommended over other methods for drought problems. Nourani et al. (2019) applied an ANN to downscale the monthly precipitation and temperature for three GCMs. Previous studies that used ANN algorithms mainly focused on utilizing a large number of large-scale variables (predictors) from GCMs over many grids surrounding the area of interest to downscale monthly precipitation (predictand). Other applications use finer resolution data such as the normalized difference vegetation index (NDVI), topography or cloud information for downscaling satellite precipitation data (Immerzeel et al., 2008).

In this study, we introduce a simple, but efficient ANN-based downscaling method that utilizes daily observed precipitation data of a pseudo-coarse-resolution (20-km) and enhances its spatial resolution to a finer original scale (5 km). During the downscaling process, it is important that the original characteristics of the 5 km precipitation data are preserved and successfully generated. This includes maintaining the extreme values of the grid, the mean, the standard deviation, and other relevant parameters. For this purpose, long-term 20-km pseudo-coarse resolution data which has been derived from spatially averaged 5-km observed data is employed. Nevertheless, it remains uncertain whether the original 5 km data can be effectively reconstructed from the synthetically upscaled 20 km data using the ANN algorithm. The object of this study is to investigate the applicability and effectiveness of the ANN-based downscaling method for maintaining the original characteristics of precipitation data under this simple scenario. The observed data set is used in this study instead of GCMs data to gain a fundamental understanding of the ANN's performance. The proposed approach eliminates the difficulties associated with predictor selection, as it only relies on the precipitation data at different spatial scales as the input for the ANN downscaling process. In addition, it has a daily downscaling time step instead of a month.

2. Overview of ANN

ANN is considered as a universal mathematical approximator. It is efficient and robust to solve large-scale nonlinear problems owing to its ability to learn and recognize the general relationship between input and output vectors. A typical ANN structure comprises an input layer, output layer, and several hidden layers. The input layer receives the input variables, which could be temperature, rainfall, water levels, or other variables in hydrological modeling. The output layer involves the values predicted by networks, which could be any variable in the hydrological response, such as streamflow or rainfall. The hidden layers contain several nodes for data processing. The number of hidden layers and nodes of each hidden layer is generally obtained via trial-and-error process (ASCE, 2000).

During the ANN modeling process, input and output data are typically divided into three sections: training, testing, and validation. Training aims to train the network to generate an output vector that is close to the target vector, and the weight and bias are optimized while minimization the error between input and output. The backpropagation algorithm with gradient descent technique is employed as one of the most common algorithms to train the network and obtain optimal weights and bias. The testing section selects the model with the best performance among various combinations of training options and prevents overfitting of the network. Such behavior can be noticed when the network tries to mimic the noisy component in individual data during the training process, rather than learning the underlying general relationship. Validation evaluates the performance of the final model using different sections of data and can be quantified by the error percentage between the desired and predicted outputs (ASCE, 2000).

3. Data and Methodology

It is worth mentioning that Kim et al. (2014) developed a downscaling method called Formatted Regression Frame (FRF) based on observed precipitation data, which takes advantage of the unique spatial correlation to downscale observed precipitation data at 20-km from a synthetically upscaled resolution of 60 km. Also, Kim et al, (2017) successfully applied the FRF method for AGCM60 data to reproduce AGCM20 precipitation data. However, the previous study used a simple linear multivariate regression, and it was for the downscaling of 60-km into 20-km resolution.

For the current study, observed gridded precipitation data (APHR_JP; Kamiguchi et. al, 2020) for 112 years from 1900 to 2011 were also utilized. The original data comprised daily precipitation and had a spatial resolution of 5 km × 5 km. First, the 5km data were upscaled to 20 km, and then the spatial correlation between the two datasets was checked for each respective region. The ANN-based regression model for downscaling was established between the upscaled 20 km and 5 km spatial resolution data. Finally, the accuracy of the downscaled 5 km precipitation data was assessed by comparing it with the original 5 km precipitation data. A square of 3 × 3 with a resolution of 20 km was considered as a downscaling frame, and the downscaling target was the center grid of this square as demonstrated in Figure. 1 The output of this model was the daily precipitation data for 16 grids at a square of 4 × 4 with a resolution of 5 km. This model was tested for five regions across Japan as shown in Figure. 1 over four different months. January represents winter, June is the rainy season due to frontal rainbands, August is the season with the most unstable atmospheric conditions, and October represents the mild weather of spring and autumn. These five regions were also chosen to observe the model's behavior in diverse environments. Regions 2~4 are the main concern as they are known for heavy rainfall, region 1 and 5 were chosen to assess the model's performance in environments with less rainfall and low temperatures, respectively.

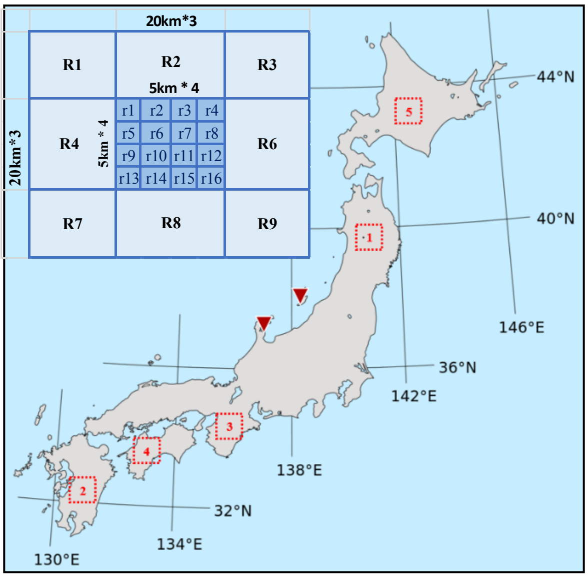


Figure 1. Locations of tested regions in Japan for ANN model. Each region is a square of 20 km x3 grid

4. ANN Setup

4.1 ANN architecture

In this study, a simple feed-forward ANN with back-propagation algorithm and stochastic gradient descent technique was used for training, as it allowed the ANN to converge and reach the global minimum more quickly (Hitokoto & Sakuraba, 2020). It comprised an input layer, single hidden layer, and an output layer, and is a widely used ANN structure in hydrological studies (Ahmed et al., 2015). The activation function is a sigmoid function that provides a nonlinear response and is one of the most commonly used activation functions in the field of hydrology (Mekanik et al., 2013).

The selection of the ANN architecture and training options is an important step, as the training results can vary based on the given ANN structures and hyper-parameters, whereas the numbers of input and output nodes depend on the number of given predictors and predictands, as illustrated in Figure. S1. There is flexibility in determining the number of hidden layers and nodes in each hidden layer. The optimal architecture is usually obtained by trial and error

(ASCE, 2000).

Seasonal data for each region were used, and divided as follows: 85 years for training (1900–1984), 12 years for testing (1985–1996), and 15 years for validation (1997–2011). Table 1 presents the daily maximum values for each stage in each region.

The standardization of data is a prerequisite for applying machine learning (ASCE, 2000). In addition, the output of the sigmoid function applied in the model ranged from 0 – 1. However, owing to the sensitivity of this function to very low and high values near 0 and 1, respectively, the input data were scaled between 0.2 and 0.8.

Table 1 Maximum daily precipitation in each stage for each season and region

Region	Data Division	Train	Test	Validation
Region_1	January	**97.48**	54.83	80.03
	June	99.44	78.61	**115.86**
	August	172.65	**195.97**	120.32
	October	**118.50**	114.15	87.60
Region_2	January	**64.80**	56.45	61.08
	June	204.83	**283.08**	213.22
	August	**301.43**	167.16	189.82
	October	**194.03**	175.18	58.70
Region_3	January	65.27	39.97	**85.77**
	June	**193.54**	225.86	185.55
	August	**211.25**	124.94	182.09
	October	**203.44**	145.50	105.05
Region_4	January	74.49	50.10	**102.92**
	June	194.84	201.02	**217.67**
	August	**284.62**	185.73	223.10
	October	**254.75**	148.74	96.32
Region_5	January	35.03	22.45	**47.27**
	June	**49.44**	41.07	44.71
	August	**155.24**	86.73	90.85
	October	**97.96**	46.95	38.78

4.2 Tuning of the hyperparameters

In this study, different combinations of hyperparameters were tested during the training process: neuron size (9, 18, 36), learning rate (0.01, 0.1, 0.8), epoch (100, 1000, 2000), and batch size (10, 20, 30). The learning rate is defined as the size of the change in each bias and weight when updated, and it also controls the size of the step taken downhill within the gradient descent. An epoch represents a complete iteration through the entire training dataset, whereas the mini-batch size is the number of samples processed before the weights and biases are updated within the model (Kim and Tachikawa, 2018). Other types of training parameters, such as the momentum and dropout ratio, were not used in this study.

In total, we used 81 cases to determine the best performance model for each season in five regions. During this process and for each case, training was conducted over a period (1900–1984), and the trained ANN was applied to the test data over a period (1985–1996) for prediction. The normalized test error (RMSE) was calculated and checked at every step so that the case of the minimum test error among the 81 cases was selected as the best combination to achieve the best result and deliver the best model for the season. This process is also important because we aimed to determine the optimal architecture for the ANN-based downscaling models for each region and calendar season by adjusting the hyperparameters, and also overcome the ANN overfitting problem as the learning rate, which controls the size of the updated weight and bias, is checked with many cases.

4.3 Model validation

Verification was performed after the training and testing using the best combination among 81 cases to determine the best performance model. The model performance was evaluated based on the RMSE criteria. Smaller values of the RMSE value indicated better accuracy and fitting of the data. It was calculated to include 0 mm/d precipitation. The RMSE indicates the general performance of the ANN model. Therefore, the bias in the average and standard deviation of the downscaled precipitation were calculated to measure the ability of the model to simulate the individual statistical properties for each season. Bias (as a percentage) for the statistic of interest is equal to the difference between the simulated and observed values divided by the observed statistic. A negative bias indicates an underestimation of precipitation, while a positive bias implies overestimation (Sachindra et al., 2018).

5. Results and Discussions

5.1 Spatial correlation

The main concept of the downscaling method proposed in this study is that the daily precipitation at a 5 km grid horizontal resolution is spatially correlated with the precipitation pattern at a 20 km resolution. As shown in Figure. S2, the correlation with 20 km grids was checked and was evidently high for all regions during all seasons.

The correlation in the winter season (October) is stronger than in the summer (June). This has a significant impact on the output of the ANN model.

5.2 Tuning of the hyperparameters

Figure. S3 shows the normalized test errors for all regions. The test error is presented in a normalized form (using scaled data within 0.2–0.8) to eliminate the impact of varying precipitation magnitudes across regions and seasons. In all the regions, the median of the boxplots is close to zero, indicating good training results. These regions are located in southwest Japan and experience the same weather and atmospheric conditions.

Table 2 lists the optimal hyperparameter combinations chosen by the ANN for each region. Regions 1 and 2 share the same combination for all seasons, except August, with 36 neurons instead of 9. In region 3, January has a different combination of (36, 0.01, 1000) for the neuron size, learning rate, and epochs, respectively. Region 4 has the same combination for all seasons except January and October, with 36 neurons. Region 5 shows greater consistency for all seasons. They represent the optimal architecture for ANN-based downscaling models for each region and calendar season.

Table 2 Optimal hypermeters for each region

Best hyper-parameters	Neurons' size in the hidden layer	learning rate	Epoch size	batch size
Region 1	9, 36	0.8	2000	10
Region 2	9, 36	0.8	2000	10
Region 3	9, 36	0.8,0.01	1000, 2000	10
Region 4	9, 36	0.8	2000	10
Region 5	9	0.8	2000	10

5.2 Analysis of the validation results

The model performance was further verified using 15 years of separate validation data for each season and region. Figure. 2 illustrates the representative results for ANN based downscaling model from region 2, for some grids (r5, r6, and r15) for the two seasons of January and June during the validation stage. The red points represent the downscaled versus the original 5km daily precipitation data, while the green points represent grid R5 of 20 km versus the original 5km daily precipitation data. The red points on the graph are positioned on the 45-degree line, indicating a close match and high agreement between the downscaled and original 5km daily precipitation data for almost all seasons in all regions. However, the green points are not aligned with the 45-degree line, indicating a difference between grid R5 of 20km and the original 5km daily precipitation data as shown in Figure. 2. This evidently illustrates the clear improvement owing to downscaling used in this study.

Figure. 3 depicts the RMSE results for all seasons in the regions during the validation period. As illustrated in this figure, the June season had the highest RMSE, followed by the August season for all grids over most of the regions. This indicates that winter and wetter climates are more skillfully downscaled compared to summer and drier climate conditions, owing to their stronger connection with large-scale atmospheric circulation (Fowler et al., 2007). In region 5, the January season has the highest error, followed by August, owing to different weather conditions, i.e., snowing. Regions 2, 3, and 4 have higher RMSE than regions 1 and 5. This can be explained by the severe rainfall events caused by the frequent typhoons that occur in these regions. Across all regions and seasons, the RMSE varies between 0.12 – 3.4 mm/day, with the lowest observed in June in region 5, and the highest observed in region 2. The maximum RMSE for regions 1 and 5 does not exceed 1.3 mm/day and 0.5 mm/day, respectively. Table 3 displays the values of RMSE as an average of 16 grids for each region. The

RMSE varies between 0.17 – 1.92 mm/day. These reflect the temporal and spatial changes in precipitation owing to seasonal variations within the same region, as well as regional variations. These changes occur because of varying weather and climatic conditions throughout Japan. It is noteworthy that some grids have higher RMSE values than others, possibly owing to differences in topography, land cover, and land-use characteristics, as each grid has a horizontal resolution of 5 km.

Finally, the bias in the mean and the standard deviation over the validation period (15 years) for all regions considering all seasons was within ±8%, as shown in Figure. S4 and Figure. S5. Some regions, such as region 5, show less bias in the mean with ± 2. The highest bias in the mean was found in regions 2 and 3. The mean is mainly underestimated in October, region 2 with (-8%). The standard deviation is evidently underestimated for the October and January seasons in region 3 and January in region 5 by -6%, -8%, and -8%, respectively. Nonetheless, the ANN-based downscaling model successfully preserves the statistical properties of the original daily data. According to Sachindra et al. (2018), the mean is better estimated regardless of the climate regime and machine learning technique employed in their study, whereas the standard deviation, maximum values, and trend of high percentiles (above the 90th percentile) of monthly precipitation are underestimated. Our study showed that the ANN model effectively estimates both the mean and variance of the original daily data.

5.3 Comparing the training, test, and validation RMSE.

For all regions and seasons, it was observed that when the maximum precipitation value (Pmax) from 112 years of data was included in the test stage, the RMSE for all the grids in this stage was higher than the combined RMSE of the validation and training stages. Similarly, if Pmax was in the validation stage, the RMSE exceeded the RMSE of the training and test stages for all grids. This affects model performance and downscaling results.

Figure. S6 displays RMSE for three stages for three months: August, June, and January in three regions 1, 2 and 4, respectively, when Pmax is

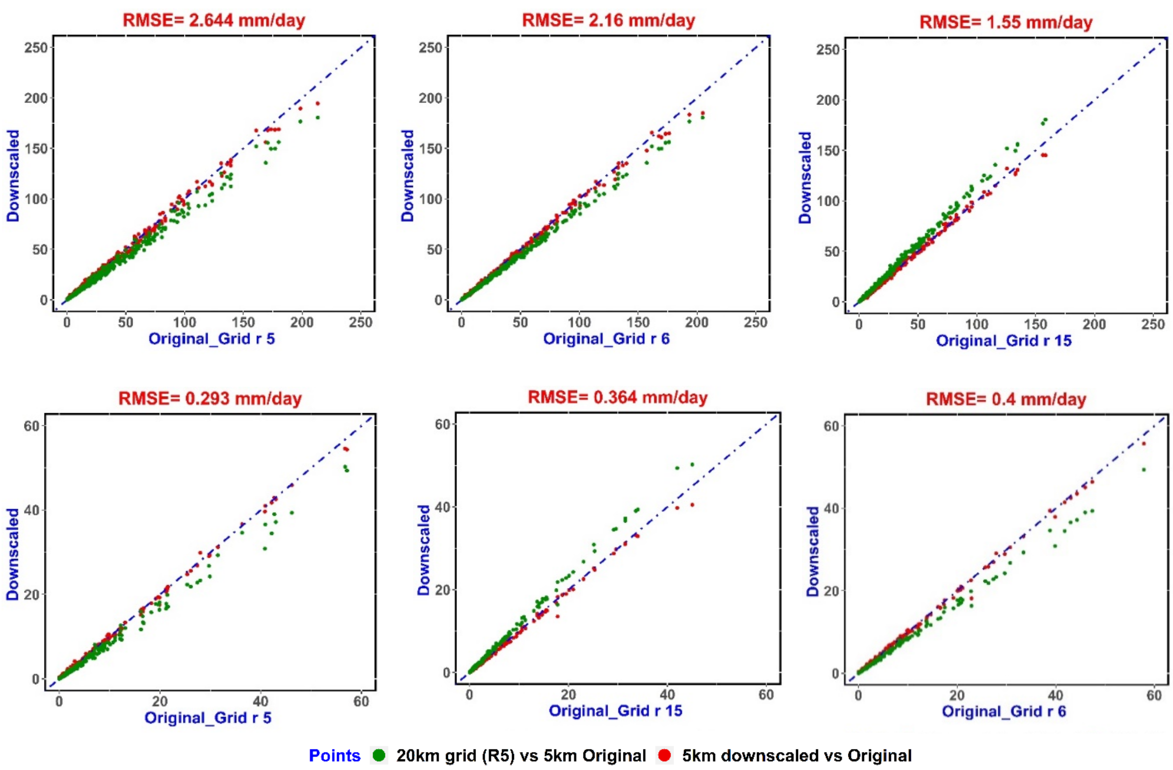
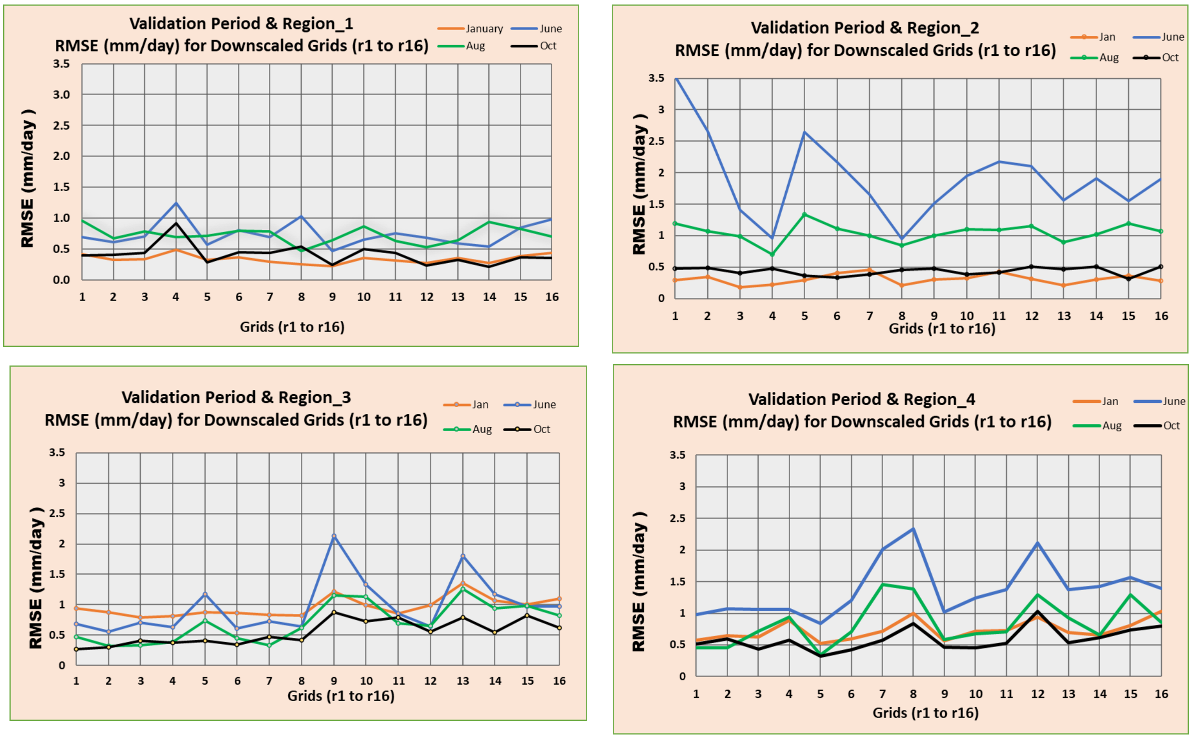


Figure 2. Scatter plot of downscaled vs original 5km daily precipitation values (red), and its own 20 km grid R5 vs original 5km daily precipitation (green) for some grids (r5, r6, r15) in two seasons **June** (first row) and **January** (second row) in region 2 in the validation stage.



included and excluded from the training stage. In August region 1 and June region 2, Pmax is included in the test stage while in January in region 3 Pmax is included in the validation stage. As shown in this Figure. S6 (left side), RMSE test error for all the grids surpassed the training and validation errors in August region 1 and June region 2, while RMSE validation errors is higher than combined training and test errors.

The year with the Pmax value has been artificially excluded from the test or validation and added to the training stage. Significant improvement in RMSE values is observed when Pmax is included in the training, as shown in Figure. S6 (right side). Consequently, the RMSE decreased across all grids during the test and validation stages. Specifically, for June in region 2, the RMSE decreased from 3.4 to 2.29 mm/day during the validation stage.

Figure. S7 displays the downscaled and observed maximum daily precipitation for each year for June in region 2 before and after including Pmax in the training stage. The figure demonstrates that the ANN model is well capturing maximum daily precipitation for both cases, but less for very extreme cases. Sharifi et al. (2019) demonstrated that the ANN model was ineffective in accurately depicting extreme monthly precipitation cases.

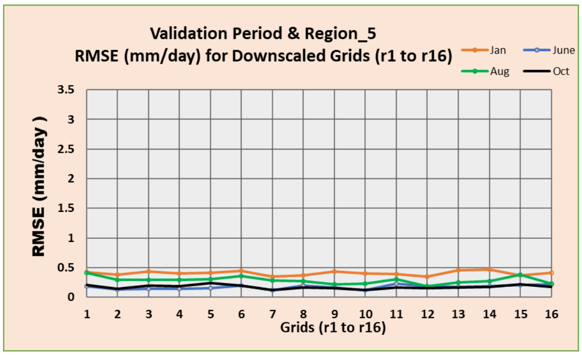


Figure 3. Plots of RMSE for 5 km grids from (r1 to r16) during all seasons in all regions 1,2 ,3,4, and 5 in the validation stage.

Table 3 Average RMSE values of 16 grids over all regions, *RMSE (unit: mm/day)*

Season	Jan	June	Aug	Oct
Region 1	0.34	0.74	0.73	0.41
Region 2	0.31	1.91	1.05	0.44
Region 3	0.96	0.97	0.70	0.55
Region 4	0.71	1.38	0.84	0.58
Region 5	0.41	0.17	0.28	0.17

Finally, obtaining the maximum precipitation dataset at the training stage is crucial and affects

6. Concluding Remarks

The current study presents a simple but efficient ANN method for downscaling daily observed precipitation at two distinct spatial resolutions: 5-km and synthetically upscaled 20-km. By comparing the downscaled 5 km precipitation data for each grid with its own 20 km grid, clear improvement was achieved by the downscaling method for almost all grids from r1 to r16 in the tested regions considering all seasons. The June season had the maximum RMSE of 3.4 mm/day. Additionally, the ANN model successfully preserved the statistical properties of the original daily data, maintaining bias in mean and standard deviation within ±8%. This model performs better in estimating maximum values. It effectively addresses several limitations and requirements associated with conventional downscaling methods. It neither utilizes a considerable number of large-scale predictors over many grids for the area of interest nor depends on assumptions such as the normal distribution of variables and the linear relationship between predictors and predictands.

Given the encouraging results obtained from the observed data, the proposed ANN method exhibits a high potential to be applied for 20-km and 5-km AGCMs data for our next study. However, there are certain limitations in this study. Firstly, the proposed method has been evaluated using only observed precipitation data. Even though the method shows successful reconstruction of coarse-resolution precipitation data into fine-resolution data, it is based on daily precipitation data. Application to hourly data might ask for more sophisticated model structures. Secondly, AGCM output from different models and resolutions would provide diverse characteristics of its precipitation output. Revision of the model structure as well as careful input selection might be necessary for applying the proposed method to AGCM output, which will be the focus of our future research.

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Appendix

In this appendix, we present supplementary figures that provide further support and information relevant to the main findings and discussions presented in the main text and contribute to a comprehensive understanding of our research.

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